

A NOTE ON THE SPECIFIC SOURCE IDENTIFICATION PROBLEM IN FORENSIC SCIENCE IN THE PRESENCE OF UNCERTAINTY ABOUT THE BACKGROUND POPULATION

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A goal in the forensic interpretation of scientific evidence is to make an inference about the source of a trace of unknown origin. The evidence is composed of the following three elements: (a) the trace of unknown origin, (b) a sample from a specific source, and (c) a collection of samples from the alternative source population. The inference process usually considers two propositions. The first proposition is usually referred to as the prosecution hypothesis and states that a given specific source is the actual source of the trace of unknown origin. The second, usually referred to as the defense hypothesis, states that the actual source of the trace of unknown origin is another source from a relevant alternative source population. One approach is to calculate a Bayes Factor for deciding between the two competing hypotheses. This approach commonly assumes that the alternative source population is completely known or uses point estimates for its parameters. Contrary to this common approach, we propose a development that incorporates the uncertainty on the alternative source population parameters in a reasonable and coherent manner into the Bayes Factor. We will illustrate the resulting effects on the calculation of several Bayes Factors for different situations with a well-studied collection of samples of glass fragments.

1. The Identification of Source Problem. The goal of a forensic scientist is help decide between two competing forensic hypotheses, one presented by the prosecution, denoted H_p , and one by the defense, denoted H_d . Sampling models corresponding to each of the forensic hypotheses are denoted M_p and M_d , respectively. The statement of the forensic hypotheses and the sampling models depends upon the source identification question being asked to the scientist. The specific source identification question considers whether the trace originates from a fixed specific source. For the specific source identification problem, the corresponding forensic hypotheses and sampling model statements are given below¹.

Forensic Hypotheses ²

H_p : The trace originated from the specific source.

H_d : The trace did not originate from the specific source, but from another source in the relevant alternative source population.

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¹The specific source identification problem can be contrasted with the common source identification problem which seeks to answer the question of whether or not two traces of unknown origin share a common source. In the common source case, the source is not fixed.

²The forensic hypotheses for the common source problem are given by

H_p : The two traces originated from the same source.

H_d : The two traces originated from two different sources.

Sampling Models ³

M_p : The trace and the control samples were both generated by the specific source.

M_d : The trace was not generated by the specific source, but generated by some other randomly selected source in the relevant alternative source population.

Two types of information exist in a case to support either the defense hypothesis or the prosecution hypothesis, quantifiable and conceptual [Aitken and Taroni (2004)]. The conceptual information includes relevant background and circumstantial information, and is denoted I . All the pieces of quantifiable information gathered in relation to a specific trace are collectively called the evidence, denoted E . For statistical purposes, E is a set of random elements, whereas I is a set of constraints that determine the form of the sampling models for E .

The evidence in the specific source problem is composed of three elements, $E = \{E_u, E_s, E_a\}$, where E_u denotes a set of observations made on objects from an unknown source, E_s denotes a set of observations made on objects from a fixed specific source, and E_a denotes a set of observations made on objects from a relevant population of possible alternative sources. For the specific source models, we are assuming that E_u , E_s , and E_a are three independent samples drawn in the following way:

1. E_s is a simple random sample from a given specific source determined by M_p . Let θ_s denote the parameters necessary to describe this sampling induced distribution.
2. E_a is constructed by first taking a simple random sample of sources from a given relevant population of alternative sources; then from each sampled source we have a simple random sample. Let θ_a denote the parameters necessary to describe this sampling induced distribution.
3. E_u is a simple random sample from a single source. It is unknown whether the source of E_u is the specific source determined by M_p or if E_u typically arises from a randomly selected source in the relevant population of possible alternative sources. The sampling distribution of E_u is characterized by either the parameters θ_s under M_p or θ_a under M_d .

Given the background information I , it is assumed that E_s contains no further information about θ_a and conversely, that E_a contains no further information about θ_s . For the purpose of this paper, we will limit ourselves to the models described above. When the specific source identification problem deviates from the models described above, for example when θ_a only contains information on the means of the sources in the alternative population, then the statistical methods will tend to be more complicated than those that follow for this development.

In most approaches used to compare the prosecution and defense models, point estimates are used for parts, or all, of the parameters describing the distribution of the evidence. In particular, several authors suggest to calculate Bayes Factors for deciding between the two models [Aitken and Stoney (1991)]. However, they assume that θ_a is known, or they estimate it from the data within a nominal degree of uncertainty. This approach leads to a Bayes Factor that is intractable and often unfeasible to calculate, especially when the evidence is high-dimensional. In this paper, we propose a factorization of the Bayes Factor that accounts for the uncertainty on the θ_a in a reasonable and coherent manner and which can be calculated in practical situations.

³The sampling models for the common source problem are given by

M_p : The two traces were generated by the same randomly selected source in the relevant alternative source population.

M_d : The two traces were generated by two different randomly selected sources in the relevant alternative source population.

2. Notational Conventions. We use the following conventions for distinguishing between sampling-induced probability and probability used as a measure of belief:

1. Latin letters denote sampling induced probability measures; for example, $f(e_s|\theta_s)$ denotes the likelihood of observing the realized value of the sample from the specific source given the actual value of the specific source distribution parameters.
2. Greek letters denote a probability measure that is a measure of belief; for example, $\pi(\theta_s|e_s)$ denotes the posterior density of $\theta_s|e_s$, which describes our belief about the value of θ_s after observing a sample $E_s|\theta_s$.
3. When combining a belief with a sampling induced probability through Bayes theorem, the result is another belief that is informed or updated by the observed sample. We denote the resulting distribution with a π .

In this setting, the stochastic nature of the evidence E is characterized by an unknown but fixed set of parameters θ . However, θ is usually of interest only in so far as knowledge of its value facilitates the quantification of support that E provides for either the prosecution hypothesis or the defense hypothesis. In this sense, having to estimate θ is a nuisance, and hence in the statistical nomenclature these parameters in this situation are known as ‘*nuisance parameters*’. The application of Bayesian methods to our problem requires us to specify priors for these nuisance parameters; one summarizing our belief about how the specific source generates evidence, $\pi(\theta_s)$, and another summarizing our prior belief about how the alternative source population stochastically generates evidence, $\pi(\theta_a)$.

3. Statistical Methods.

3.1. Introduction to the Bayes Factor. Dating back to the 1970’s, the specific source identification problem has been approached within the context of subjective Bayesian forensic hypothesis testing (See [Aitken and Stoney \(1991\)](#), [Lindley \(1977\)](#), and [Shafer \(1982\)](#) for more details). Historically, the specific source identification problem has been limited to applications in which the data is inherently low dimensional, the stochastic nature of the evidence can be characterized by a common parametric family of distributions, and the evidence from the alternative source population is sufficiently precise that it completely characterizes the stochastic nature of the alternative source population. By approaching the specific source identification problem as a Bayesian hypothesis test, the forensic statistician is tasked with providing a summary of the scientific evidence that is logical and coherent for updating a prior belief structure concerning the two competing hypotheses. The summary is typically known as a Bayes Factor [[Good \(1991\)](#)]. Traditionally, this summary is used within the context of a Bayes’ rule as follows:

$$(3.1) \quad \underbrace{\frac{P(H_p|e, I)}{P(H_d|e, I)}}_{\text{Posterior Odds}} = \underbrace{\frac{P(e|H_p, I)}{P(e|H_d, I)}}_{\substack{\text{Bayes Factor and/or} \\ \text{Likelihood Ratio}}} \times \underbrace{\frac{P(H_p|I)}{P(H_d|I)}}_{\text{Prior Odds}},$$

where e is the realization of the evidence, H_p is the prosecution hypothesis, H_d is the defense hypothesis, and I is the relevant background information common to both hypotheses. The prior odds summarize our relative belief concerning the validity of the prosecution and defense forensic hypotheses before observing the evidence.

The Bayes Factor then allows us to update our belief following the observation of the evidence and arrive at the posterior odds concerning the relative validity of the two hypotheses. If the Bayes Factor (and the corresponding posterior odds) is sufficiently high, then we support the prosecution

hypothesis; on the other hand if it is sufficiently close to zero, we support the defense hypothesis. In effect the Bayes Factor is providing a numerical summary of the answer to both of these questions:

“What is my belief about the likelihood of observing the evidence under the prosecution hypothesis?”

versus

“What is my belief about the likelihood of observing the evidence under the defense hypothesis?”

It is extremely important note that the use of a Bayes Factor in the context of formal Bayesian model selection, two sets of probability measures are required. The first is the prior beliefs concerning the relative validity of the two competing models, which has been described as the prior odds in Equation 3.1. The second is a set of priors that characterizes the belief about the parameters for the stochastic generation of the evidence under the prosecution and defense models. Since the main focus of this paper is to study the Bayes Factor for the specific source identification problem under certain conditions, we will only discuss the second set of priors for characterizing the parameters of the sampling models.

3.2. Known Alternative Source Population Parameters. As an introduction to derivations associated with the Bayes Factor for the specific source identification problem, we will derive the value of evidence as presented by Lindley (1977). In this section we are assuming that we have a well-studied alternative source population with known parameters, θ_{a_0} . The only unknown parameters that are contributing to the uncertainty about the value of the evidence are the ones associated with the specific source, θ_s . Let $e = \{e_s, e_u, e_a\}$ represent the realization of the random element E for a specific case at hand. Let $\theta = \{\theta_s, \theta_{a_0}\}$ and $\pi(\theta) = \pi(\theta_s)$ be a probability distribution used to describe our prior belief about θ since there is no uncertainty about θ_{a_0} .

Define the value of the evidence as

$$(3.2) \quad V_{ss}(e) = \frac{\pi(e|H_p, I)}{\pi(e|H_d, I)}.$$

Computing the value of evidence in this form involves evaluating the likelihood of the entire set of evidence e . This can be computationally intensive and often unfeasible. To obtain a computationally tractable form of the value of evidence, Aitken and Taroni (2004) have proposed a factorization of $V_{ss}(e)$ which assumes that θ_a is known or can be estimated from the data. The factorization develops as follows:

$$\begin{aligned} V_{ss}(e) &= \frac{\pi(e|M_p)}{\pi(e|M_d)} && \text{see Note 1 below} \\ &= \frac{\int f(e|\theta, M_p)\pi(\theta|M_p)d\theta}{\int f(e|\theta, M_d)\pi(\theta|M_d)d\theta} && \text{see Note 2 below} \\ &= \frac{\int f(e_u|\theta, M_p)f(e_s|\theta, M_p)f(e_a|\theta, M_p)\pi(\theta)d\theta}{\int f(e_u|\theta, M_d)f(e_s|\theta, M_d)f(e_a|\theta, M_d)\pi(\theta)d\theta} && \text{see Note 3 below} \\ &= \frac{\int f(e_u|\theta_s)f(e_s|\theta_s)f(e_a|\theta_{a_0})\pi(\theta_s)d\theta_s}{\int f(e_u|\theta_{a_0})f(e_s|\theta_s)f(e_a|\theta_{a_0})\pi(\theta_s)d\theta_s} && \text{see Note 4 below} \\ &= \frac{f(e_a|\theta_{a_0}) \int f(e_u|\theta_s)f(e_s|\theta_s)\pi(\theta_s)d\theta_s}{f(e_u|\theta_{a_0})f(e_a|\theta_{a_0}) \int f(e_s|\theta_s)\pi(\theta_s)d\theta_s} \\ &= \frac{1}{f(e_u|\theta_{a_0})} \times \frac{\int f(e_u|\theta_s)f(e_s|\theta_s)\pi(\theta_s)d\theta_s}{\int f(e_s|\theta_s)\pi(\theta_s)d\theta_s} && \text{see Note 5 below} \end{aligned}$$

$$\begin{aligned}
&= \frac{1}{f(e_u|\theta_{a_0})} \times \int f(e_u|\theta_s) \frac{f(e_s|\theta_s)\pi(\theta_s)}{\int f(e_s|\theta_s)\pi(\theta_s)d\theta_s} d\theta_s \\
&= \frac{\int f(e_u|\theta_s)\pi(\theta_s|e_s)d\theta_s}{f(e_u|\theta_{a_0})} && \text{see Note 6 below} \\
&= \frac{\pi(e_u|e_s, M_p, I)}{f(e_u|\theta_{a_0})} && \text{see Note 7 below}
\end{aligned}$$

NOTE 1. We can drop the conditional notation on I since the background information will be the same for both the prosecution and the defense and the relevant information has been considered in the models.

NOTE 2. The definition of the marginal belief of X given some parameter ϕ is $\pi(x) = \int f(x|\phi)\pi(\phi)d\phi$.

NOTE 3. $f(e|\theta)$ is the likelihood function for observing e . Therefore, $f(e|\theta) = f(e_u|\theta)f(e_s|\theta)f(e_a|\theta)$. Also, $\pi(\theta)$ does not depend on M_p or M_d so the conditional notation can be dropped.

NOTE 4. By definition of $\pi(\theta) = \pi(\theta_s)$. The parameters for E_s and E_a are fixed so they will be the same for both M_p and M_d . Under the prosecution model, M_p , E_u is characterized by θ_s since the prosecution believes the specific source is the origin of the trace. Therefore, $f(e_u|\theta, M_p) = f(e_u|\theta_s)$. Under the defense model, M_d , E_u is completely characterized by θ_{a_0} since the defense believes the trace came from a source in the alternative source population. Therefore, $f(e_u|\theta, M_d) = f(e_u|\theta_{a_0})$.

NOTE 5. It should be noted that $f(e_a|\theta_{a_0})$ cancels from the value of evidence. This means that since θ_{a_0} is known, e_a is irrelevant to the resulting value of the evidence.

NOTE 6. The definition of the posterior belief of ϕ given X is $\pi(\phi|x) = \frac{f(x|\phi)\pi(\phi)}{f(x)} = \frac{f(x|\phi)\pi(\phi)}{\int f(x|\phi)\pi(\phi)d\phi}$.

NOTE 7. The definition of posterior predictive belief of Y given X is $\pi(y|x) = \int f(y|\phi)\pi(\phi|x)d\phi$.

By assuming we know (or we are certain that we know) the value θ_{a_0} , the denominator reduces to evaluating the sampling distribution of e_u ; in effect the denominator does not contain any belief measures when the alternative source population parameters are known. We will refer to

$$(3.3) \quad V_{ss}(e|\theta_{a_0}) = \frac{\pi(e_u|e_s, M_p, I)}{f(e_u|\theta_{a_0})}$$

as the factored form of the specific source value of evidence when θ_a is known.

3.3. Unknown Alternative Source Population Parameters. In this section, we propose a factorization of V_{ss} that does not assume that θ_a is known, but that is still computationally tractable. Let $e = \{e_s, e_u, e_a\}$ represent the realization of the random element E for a specific case at hand. Let $\theta = \{\theta_s, \theta_a\}$. Due to the uncertainty in the parameters θ we will need to characterize our belief about it using the prior. Let $\pi(\theta) = \pi(\theta_s)\pi(\theta_a)$ be the probability distribution used to describe our prior belief about θ . Note that we are choosing to restrict ourselves to priors on θ_s and θ_a that are *independent of each other*. Starting from the value of the evidence given by Equation 3.2, and using similar methods as the previous case, we can rewrite V_{ss} as follows:

$$\begin{aligned}
V_{ss}(e; \theta_s, \theta_a) &= \frac{\pi(e|M_p)}{\pi(e|M_d)} && \text{see Note 1 above} \\
&= \frac{\int f(e|\theta, M_p)\pi(\theta|M_p)d\theta}{\int f(e|\theta, M_d)\pi(\theta|M_d)d\theta} && \text{see Note 2 above} \\
&= \frac{\int f(e_u|\theta, M_p)f(e_s|\theta, M_p)f(e_a|\theta, M_p)\pi(\theta)d\theta}{\int f(e_u|\theta, M_d)f(e_s|\theta, M_d)f(e_a|\theta, M_d)\pi(\theta)d\theta} && \text{see Note 3 above} \\
&= \frac{\int f(e_u|\theta_s)f(e_s|\theta_s)f(e_a|\theta_a)\pi(\theta)d\theta}{\int f(e_u|\theta_a)f(e_s|\theta_s)f(e_a|\theta_a)\pi(\theta)d\theta} && \text{see Note 8 below} \\
&= \frac{\int f(e_u|\theta_s)f(e_s|\theta_s)\pi(\theta_s)d\theta_s \int f(e_a|\theta_a)\pi(\theta_a)d\theta_a}{\int f(e_s|\theta_s)\pi(\theta_s)d\theta_s \int f(e_a|\theta_a)f(e_u|\theta_a)\pi(\theta_a)d\theta_a} && \text{see Note 9 below} \\
&= \frac{\int f(e_u|\theta_s)f(e_s|\theta_s)\pi(\theta_s)d\theta_s}{\int f(e_s|\theta_s)\pi(\theta_s)d\theta_s} \times \frac{\int f(e_a|\theta_a)\pi(\theta_a)d\theta_a}{\int f(e_a|\theta_a)f(e_u|\theta_a)\pi(\theta_a)d\theta_a} \\
&= \frac{\int f(e_u|\theta_s)f(e_s|\theta_s)\pi(\theta_s)d\theta_s}{\int f(e_s|\theta_s)\pi(\theta_s)d\theta_s} \bigg/ \frac{\int f(e_a|\theta_a)f(e_u|\theta_a)\pi(\theta_a)d\theta_a}{\int f(e_a|\theta_a)\pi(\theta_a)d\theta_a} \\
&= \frac{\int f(e_u|\theta_s)\pi(\theta_s|e_s)d\theta_s}{\int f(e_u|\theta_a)\pi(\theta_a|e_a)d\theta_a} && \text{see Note 6 above} \\
&= \frac{\pi(e_u|e_s, M_p)}{\pi(e_u|e_a, M_d)} && \text{see Note 7 above}
\end{aligned}$$

NOTE 8. The parameters for E_s and E_a are fixed so they will be the same for both M_p and M_d . Under the prosecution model, M_p , E_u is characterized by θ_s since the prosecution believes the specific source is the origin of the trace. Therefore, $f(e_u|\theta, M_p) = f(e_u|\theta_s)$. Under the defense model, M_d , E_u is characterized by θ_a since the defense believes the trace came from a source in the alternative source population. Therefore, $f(e_u|\theta, M_d) = f(e_u|\theta_a)$.

NOTE 9. Since $\pi(\theta) = \pi(\theta_s)\pi(\theta_a)$, which means that θ_s and θ_a are independent, we can factor the integral apart with respect to θ into the product of the integrals for θ_s and θ_a .

We will refer to

$$(3.4) \quad V_{ss}(e) = \frac{\pi(e_u|e_s, M_p)}{\pi(e_u|e_a, M_d)}$$

as the factored form of the specific source value of evidence when θ_a is unknown.

3.4. Results of the Factored Forms for the Value of Evidence. When the value of evidence is given by Equation 3.2, the computation involves evaluating the likelihood of the entire set of evidence E . This can be very computationally intensive, and often unfeasible. In the factored forms given by Equation 3.3 and Equation 3.4, the computation only involves the posterior predictive belief of the unknown evidence. Therefore, the factored forms create a computationally feasible method of evaluating the Bayes Factor for the specific source identification problem that can be calculated using Monte Carlo integration techniques [Kass and Raftery (1995)]. When the specific source value of evidence is factored into the form given by Equation 3.3 (the case when θ_{a_0} is known or estimated from the data), e_a is irrelevant to the value of the evidence. This considerably simplifies the computational complexity of the calculation of V_{ss} ; however, the uncertainty in the estimation of θ_a is not formally accounted for. This uncertainty is taken into account when the value of evidence

is calculated using the factorization presented in Equation 3.4 (the case when the parameters for the alternative source population are unknown). In this case, Monte Carlo integration techniques have to be used for the calculation of the denominator. This involves an additional layer of computational complexity; however, modern computers can cope with the required number of computations in a reasonable amount of time.

4. Glass Example. In order to compare the value of the evidence obtained using both factorizations of V_{ss} we use a collection of samples of glass fragments studied by Aitken and Lucy (2004). The dataset consists of three classes of windows, with 16, 16, and 30 windows in each class. There are 5 glass fragments per window. Following Aitken and Lucy (2004), we consider the logarithm of the measurements for the ratios of elemental compositions on each glass fragment: $\log(Ca/K)$ is represented by the second variable (V2), $\log(Ca/Si)$ is represented by the third variable (V3), and $\log(Ca/Fe)$ is represented by the fourth variable (V4).

As an illustrative example of computing the value of evidence for the specific source identification problem we focus only on the first class of 16 windows, and we consider two scenarios. For the first scenario, e_u and e_s will share a fixed source, with the 4th window playing the role of the specific source. The first three fragments from window 4 will serve as e_s and the last two fragments from window 4 will serve as e_u . For the second scenario, e_u and e_s will have different sources. The first three fragments from window 4 will serve as e_s and two fragments from the 2nd window will serve as e_u . In both scenarios, the remaining 70 glass fragments divided among the 14 remaining windows will serve as e_a . The pairwise scatter plots of the evidence under each scenario can be seen in Figure 1.

The specific source identification question for this example can stated as

“Did the glass fragments of unknown source come from the fourth window?”

The resulting forensic hypotheses are

H_p : The glass fragments from the unknown source came from the fourth window.

H_d : The glass fragments from the unknown source did not come from the fourth window, but from some other window.

The corresponding sampling models are

M_p : The glass fragments from the unknown source came from the fourth window. Under this model, E_u can be characterized by the same model which characterizes E_s , described in detail below.

M_d : The glass fragments from the unknown source came from a randomly selected window in the alternative source population. Under this model, E_u can be characterized by the same model which characterizes E_a , described in detail below.

4.1. Sampling Model for the Evidence from the Specific Source. First, we will assume that the measurements on the glass fragments composing e_s are an independent and identically distributed, abbreviated i.i.d., sample from a multivariate normal with a mean vector μ_s and covariance Σ_s . Let y_{sj} denote the vector of measurements on the j^{th} fragment from the specific source evidence for $j = 1, 2, \dots, m$ (for this example $m = 3$), then y_{sj} follows a multivariate normal distribution with a mean vector, μ_s , and a covariance matrix, Σ_s , which we will denote as $y_{sj} \sim MVN(\mu_s, \Sigma_s)$. For this example, the specific source population parameters are $\theta_s = \{\mu_s, \Sigma_s\}$, so we need to specify priors for both μ_s and Σ_s . We will use a relatively non-informative multivariate normal prior on μ_s with the zero mean vector and a diagonal covariance matrix with diagonal elements equal to 3000. The prior for Σ_s is an Inverse Wishart distribution (denoted W^{-1}) centered at a diagonal

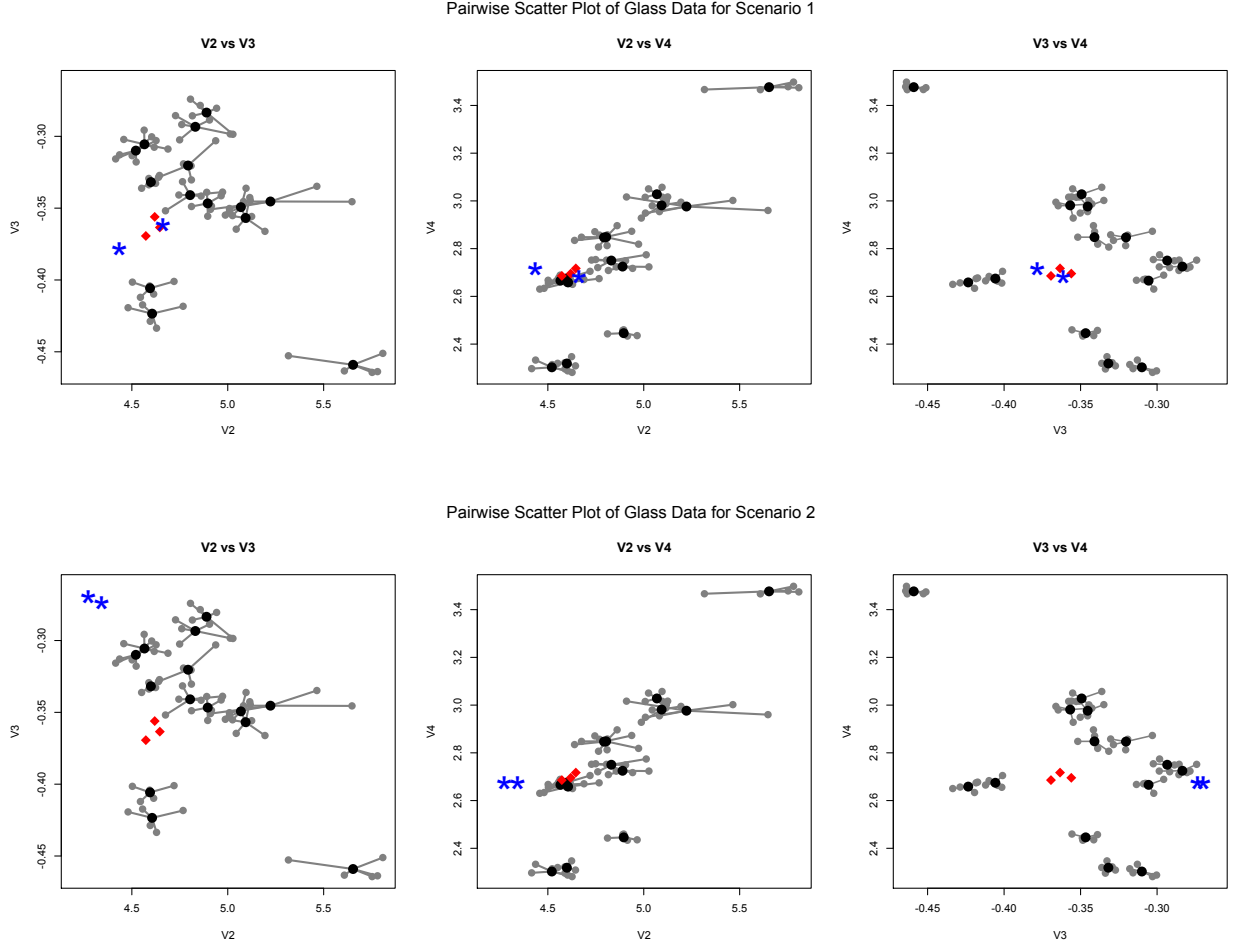


FIG 1. In the pairwise scatterplots of the evidence E , the blue asterisks represent E_u , the red diamonds represent E_s , and the gray dots represent E_a . The large black dots are the mean values for each window and the gray lines show the deviation from that mean for each fragment from the window.

covariance matrix, Φ with diagonal elements of 0.01, 0.00005, 0.0005 and three degrees of freedom. These diagonal elements were chosen based on the approximate precision of the measurements for the evidence. The full model for E_s with supporting prior beliefs is summarized below.

$$y_{sj} \sim \text{MVN}(\mu_s, \Sigma_s)$$

$$\mu_s \sim \text{MVN}(0, 3000I)$$

$$\Sigma_s \sim W^{-1}(\Phi, 3)$$

It should be noted that any number of reasonable priors can be chosen for μ_s and Σ_s . The numerator for the values of evidence $\pi(e_u|e_s, M_p)$ under scenario 1 (*Exp 1*) and scenario 2 (*Exp 2*) are given in Table 1 and Table 2 below.

4.2. *Sampling Model for the Evidence in the Alternative Source Population.* Next, we assume that the measurements on the glass fragments composing e_a follow a hierarchical multivariate normal model with the assumption that all windows in the alternative source population have a

mean μ_a , a within-covariance matrix Σ_w , and a between source covariance matrix Σ_b . Let y_{ij} denote the vector of measurements on the j^{th} fragment, for $j = 1, 2, \dots, m_i$ (for this example, $m \equiv m_i = 5$ for all i) from the i^{th} window, for $i = 1, 2, \dots, n$ (for this example, $n = 14$). The hierarchical multivariate model in this case is a simple random effects model where the between-source effects a_i are i.i.d. multivariate normal random vectors with a mean vector of zero and a covariance matrix Σ_b . The within-source effects w_{ij} are assumed to be i.i.d. multivariate normal vectors with a mean vector of zero and a covariance matrix of Σ_w . We will compare the results of both scenarios described above under two different conditions. First, the alternative source population parameters are assumed to be known. Secondly, the alternative source population parameters are assumed to be unknown.

When the alternative source population parameters $\theta_a = \{\mu_a, \Sigma_b, \Sigma_w\}$ are assumed to be known, we use the estimates for the parameters as suggested in [Aitken and Lucy \(2004\)](#). The estimates $\hat{\theta}_a = \{\hat{\mu}_a, \hat{\Sigma}_b, \hat{\Sigma}_w\}$ of the known parameters are summarized below.

$$\begin{aligned}\hat{\mu}_a &= \frac{1}{mn} \sum_{i=1}^n \sum_{j=1}^m y_{ij} \\ \bar{y}_i &= \frac{1}{m} \sum_{j=1}^m y_{ij} \\ \hat{\Sigma}_w &= \frac{1}{n(m-1)} \sum_{i=1}^n \sum_{j=1}^m (y_{ij} - \bar{y}_i)(y_{ij} - \bar{y}_i)^T \\ \hat{\Sigma}_b &= \left[\frac{1}{n-1} \sum_{i=1}^n (\bar{y}_i - \hat{\mu}_a)(\bar{y}_i - \hat{\mu}_a)^T \right] - \left[\frac{1}{m} \hat{\Sigma}_w \right]\end{aligned}$$

The denominator for the values of evidence $f(e_u|\hat{\theta}_{a_0})$ under scenario 1 (*Exp 1*) and scenario 2 (*Exp 2*) are given in Table 1 below.

TABLE 1
Alternative Source Population Parameters Known

	<i>Exp 1</i>	<i>Exp 2</i>
$\pi(e_u e_s, M_p)$	119740.3	2.316277
$f(e_u \hat{\theta}_{a_0})$	582.6974	144.1683
$V_{ss}(e \hat{\theta}_{a_0})$	205.4931	0.01606648

When the alternative source population parameters $\theta_a = \{\mu_a, \Sigma_b, \Sigma_w\}$ are unknown, our prior for Σ_w is the same that is used for Σ_s , and the prior for μ_a is the same as that used for μ_s . We use an Inverse Wishart prior for Σ_b centered at the identity covariance matrix with three degrees of freedom. The full model for E_a with supporting prior beliefs is summarized below.

For $i = 1, 2, \dots, 14$ and $j = 1, 2, 3, 4, 5$:

$$\begin{aligned}y_{ij} &= \mu_a + a_i + w_{ij} & \mu_a &\sim MVN(0, 3000I) \\ a_i &\stackrel{iid}{\sim} MVN(0, \Sigma_b) & \Sigma_b &\sim W^{-1}(I, 3) \\ w_{ij} &\stackrel{iid}{\sim} MVN(0, \Sigma_w) & \Sigma_w &\sim W^{-1}(\Phi, 3)\end{aligned}$$

The denominator for the values of evidence $\pi(e_u|e_s, M_p)$ under scenario 1 (*Exp 1*) and scenario 2 (*Exp 2*) are given in Table 2 below.

The computations were performed on a 2012 MacBook Pro with an OS X 10.8.5 operating system, 2.3 GHz Intel Core i7 processor, and 16 GB, 1600 MHz memory using R version 3.0.2.

TABLE 2
Alternative Source Population Parameters Unknown

	<i>Exp 1</i>	<i>Exp 2</i>
$\pi(e_u e_s, M_p)$	119740.3	2.316277
$\pi(e_u e_a, M_d)$	30.17140	209.5902
$V_{ss}(e)$	3968.669	0.01105146

All posterior predictive distributions for the parameters are estimated using the “MCMCglmm” package in R [Hadfield (2010)]. Using the parameter values sampled from these posterior predictive distributions, we estimated the posterior predictive beliefs of e_u for the values of evidence using a standard Monte Carlo average integration technique. The Monte Carlo estimates were based on a sample size of 29,000 (30,000 iterations with a burn-in of 1000). We also made use of the matrix form of the multivariate simple random effects models as presented by Miller (1977) (See the Appendix for details).

5. Discussion. In the illustrative example described in Section 4, the behavior of V_{ss} is consistent between the calculations when the alternative source population parameters are assumed to be known (results for this experiment can be found in Table 1) and when the alternative source population parameters are unknown (results for this experiment can be found in Table 2). The value of evidence for the first scenario suggests in both cases that the evidence is more likely to have been generated according to the prosecution model than by the defense model (since the values of evidence are significantly greater than one); the value of the evidence for the second scenario suggests in both cases that the evidence is more likely to have arisen under the defense model. These results were expected by the design of the experiment. However, by contrasting the likelihood of the evidence under the defense model in Table 1 and Table 2, we observe that in the first scenario the evidence is more likely when the alternative source population parameters are known than when they are not, while in the second scenario the evidence is more likely when there is uncertainty on the alternative source population parameters. When the number of observations in the alternative source population is small, there is a marked difference between these values which suggests that using the estimates of the parameters is not a reasonable surrogate for calculating the value of the evidence in the presence of uncertainty in the alternative source population parameters. We expect that the difference between $V_{ss}(e; \hat{\theta}_{a_0})$ and $V_{ss}(e)$ will go to zero as the amount of evidence about the alternative source population becomes large (the rate of convergence is currently being investigated by the authors). In practice, the use of estimates of the known parameters for the alternative source population may lead to grossly over- or under-estimating the value of the evidence. The direction of the misleading effect will depend upon the rarity of the characteristics of e_u in the alternative source population. This effect may ultimately mislead the criminal justice system.

It should be noted that choosing different priors for the model parameters can result in radically different values of evidence. Additionally, when the alternative source population parameters are unknown there is less freedom in choosing the priors than when the parameters are known. In order for the factorization of the value of evidence to hold when there is uncertainty in the alternative source population parameters, the prior for the specific source parameters, $\pi(\theta_s)$, must be chosen to be independent from the prior for alternative source parameters, $\pi(\theta_a)$. This precludes the use of the popular “random man” prior for the specific source parameters in which the specific source is believed to be typical of the alternative source population.

6. Conclusion. Computing the value of evidence when it is given by its raw form (Equation 3.2) requires evaluating the likelihood of the entire set of evidence. In most situations, this

evaluation is computationally unfeasible. However, when the value of evidence is given in the factored forms (Equation 3.3 and Equation 3.4) it can be approximated using Monte Carlo integration techniques [Kass and Raftery (1995)]. In the rare setting when there is no uncertainty about the alternative source population parameters (Equation 3.3), it is not surprising that including e_a in the calculation of the value of evidence has no impact. However, in traditional forensic settings, there is rarely sufficient information about the alternative source population parameters to assume that it is possible to estimate them accurately; henceforth, such situations require a novel approach.

In this paper, we develop a logical and coherent method which formally incorporates the uncertainty on the alternative source population parameters into the calculation of the Bayes Factor. This is a major departure from the ad-hoc approaches to include uncertainty about the background population in the value of the evidence that are currently available in the forensic statistics literature. These methods typically entail the construction of a confidence or credible interval for the likelihood ratio represented by $V_{ss}(e; \hat{\theta}_{a_0})$. By formally incorporating uncertainty about e_a into the value of evidence we can guarantee that the resulting value is statistically rigorous and that the decisions based on it will be admissible in a statistical decision theoretic sense. To avoid potentially misleading decisions in the court system, the authors suggest replacing the use of ad-hoc methods with the statistically rigorous methods presented here when there is uncertainty in the alternative source population parameters.

APPENDIX A

We will summarize a well-known result from Miller concerning the matrix form of the multivariate simple random effects model [Miller (1977)]. Let y_{ij} denote the k -dimensional vector of measurements on the j^{th} component from the i^{th} source for $j = 1, 2, \dots, m_i$ and $i = 1, 2, \dots, n$. Then the simple random effects model is given by

$$y_{ij} = \mu_a + a_i + w_{ij}$$

where $a_i \stackrel{iid}{\sim} N_k(\mathbf{0}, \Sigma_a)$ and $w_{ij} \stackrel{iid}{\sim} N_k(\mathbf{0}, \Sigma_w)$ are independent from each other. It is often useful to think about the random effects model as a combined multivariate normal random vector. If y_{ij} follows a simple random effects model, then the vector $Y_i = (y_{i1} \ y_{i2} \ \dots \ y_{im_i})^T$ has the following distribution:

$$Y_i \stackrel{iid}{\sim} N_k(\mu_c, \Sigma_c)$$

$$\text{where } \Sigma_c = \begin{pmatrix} \Sigma_a + \Sigma_w & \Sigma_a & \dots & \Sigma_a \\ \Sigma_a & \Sigma_a + \Sigma_w & \ddots & \vdots \\ \vdots & \ddots & \ddots & \Sigma_a \\ \Sigma_a & \dots & \Sigma_a & \Sigma_a + \Sigma_w \end{pmatrix} \text{ and } \mu_c = \begin{pmatrix} \mu_a \\ \mu_a \\ \vdots \\ \mu_a \end{pmatrix} \text{ for } i = 1, 2, \dots, n.$$

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